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Farm performance analysis: Technical efficiencies and technology gaps of Nepalese farmers in different agro-ecological regions

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ABSTRACT

This paper employs a stochastic metafrontier framework to examine technical efficiencies and technology gaps of Nepalese farmers in different agro-ecological regions. On average, the technical efficiency level derived from the regional frontier is 81%, from the metafrontier it is 57%, and the technological gap ratio is 70%. There is therefore a clear opportunity to improve the performance of farming households within regions through improving farmer's education, farming experiences, and by adopting climate change adaptation practices. Also indicated is that agricultural policies should be developed to reduce the technology gap between specific regions and the overall agricultural sector. In this context, this study highlights the need to improve farmers' access to agricultural markets, livelihood diversification and strengthening social capital such as farmers' participations in relevant agricultural organizations.

1. Introduction

Traditionally, agriculture has been an important sector of the Nepalese economy. Nevertheless, its contribution to the country's gross domestic product has dropped during recent years from 40% of GDP in 1995–33% in 2015 (MoAD, 2015). Although agriculture has special significance and economic importance, its production and productivity have not been encouraging and its rate of growth unstable – ranging from 5.8% in 2008, 4.5% in 2011, and 1.9% in 2015 (Fig. 1). At these levels agricultural sector productivity is considerably lower than other South Asian countries (Joshi et al., 2012). This low level of development is associated with the poor adoption of agricultural technologies, inefficient use of resources such as land and fertilizer, and lack of research (Adhikari and Bjorndal 2012; Bhattarai et al., 2015).

Thus, on the one hand the performance of the agriculture sector is poor, and on the other hand, there is increasing population pressure on the limited cultivable land. Moreover, as Nepal is a mountainous country, only a small proportion (20%) of the land is cultivated. Thus, the prospect of expanding agricultural land is virtually nonexistent. To meet the demand of the growing population therefore, it is necessary to increase food production through improvements in agricultural production efficiency. For these reasons, it is essential to examine and understand the causes of the inefficient use of resources in the agricultural sector. Increasing efficiency and productivity of this sector is likely to enhance subsistence farmers' opportunities to produce more and diversify farming which in turn would improve their food security and income levels (Ogundari, 2014).

Nepal is divided into three distinct agro-ecological regions (Terai, Hill, and Mountain), which differ in terms of altitude, soil types, landscapes, and climatic conditions which vary from subtropical in the lower elevations to the alpine in the higher elevations. As a consequence, there exists a marked variation in farming systems, and socio-economic conditions.[1] The aforementioned factors have led to wide heterogeneity in the available production technology set for the farming households in different ecological regions. It is important to note that the technical efficiency (TE) of farming households operating under different technologies is not comparable under the same production frontier. This is because households make choices among different sets of input-output combinations (O'Donnell et al., 2008). Therefore, an analysis of agricultural production efficiency in Nepal needs to take into account that farming households operate in different production environments which cannot be assessed under the same production frontier. One option could be to estimate different production frontiers for each region. However, the limitation of employing this approach is that TE measures cannot be compared between the regions because these TE scores are estimated relative to different production frontiers (Melo-Becerra and Orozco-Gallo, 2015). The literature on

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[1] The geographical and climatic variations lead to different level of resource endowment and production potentials which causes further variations in farming systems and socio-economic conditions. The three regions have wide variations with respect to market access as well as diversity in people's ethnicity and culture (MoF, 2015).

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Fig. 1. Economic growth rate in Nepal.

production efficiency in the agricultural sector is limited and focused on the analysis of specific crops such as rice (Piya et al., 2012), maize (Paudel and Matsuoka, 2009), and coffee (Poudel et al., 2015). It is also focused on a particular ecological region. The purpose of this study is, then, to evaluate and compare the production efficiency of farming households in the three different regions of Nepal.

The empirical analysis is carried out employing a metafrontier production function based on a stochastic frontier framework. The metafrontier approach assumes that there is some underlying common technology that makes it possible to estimate a pooled frontier. However, due to heterogeneity it is reasonable to divide farming households in to distinct groups. This is justified by the geographical variations across the agro-ecological regions in Nepal and the differences among the farming households in terms of resources and knowledge. In addition, there exist various similarities across the regions that makes it possible to estimate a pooled frontier. For instance, most farmers in all the three regions are smallholders and grow crops such as maize, wheat, buckwheat, legumes, and oilseeds. In this context, the application of a metafrontier allows the TE of farming households to be compared within each ecological region and between regions in relation to the agricultural sector as a whole. The purpose of this paper is to examine what factors are common across regions and what are region-specific. More specifically, we examine by how much the agricultural output can be improved by using the available inputs and technology within the particular regions and further by adopting the technological condition across the regions. In this context, policy makers can use the information to better guide resource allocation and enhance overall efficiency in resource use and economic well-being.

This paper is organized into five sections, in addition to the introduction. In the second section, we briefly review the literature on the metafrontier approach. The third section describes the study area, data, and methodology used in the analysis. The fourth section presents and discusses the results. The last section concludes.

2. A brief literature review of the metafrontier approach

The metafrontier production function was first purposed by Hayami (1969) and Hayami and Ruttan (1970). This function is based on the idea that all producers in the various production groups have potential access to a set of production technologies. Depending on the specific circumstances such as those relating to production environments, government regulations, production resources, and relative input prices, each producer may choose to adopt a particular technology (Huang et al., 2014). The practical applications of the metafrontier approach have existed since late 1980's and early 1990's (See e.g. Charnes et al., 1981; Grosskopf and Valdmanis 1987; Månsson, 1996). Battese and Rao (2002) introduced an application of the metafrontier which allows for the estimation and comparison of TEs among different groups. Battese et al. (2004) and O'Donnell et al. (2008) further developed the empirical application of this approach by employing a two-step procedure for estimating the metafrontier. In the first step, stochastic frontier techniques are used to estimate the group-specific frontier. In the second step, they employ mathematical programming techniques to estimate the metafrontier.

A number of empirical studies have employed the above approach. Examples include that of Moreira and Bravo-Ureta (2010) who estimate and compare the technical efficiency and metatechnology ratios for dairy farms from Argentina, Chile and Uruguay. Villano and Boshrabadi (2010) compare the performance of different Pistachio tree varieties in Iran. Villano et al. (2015) estimate and compare the technical efficiency of rice farmers in the Philippines between those who adopt certified seeds with those who don't. The difficulty with the two-step mixed approach developed by Battese and Rao (2002), Battese et al. (2004) and O'Donnell et al. (2008) is that, due to the deterministic nature of mathematical programming (linear or quadratic) in the second step, the metafrontier estimators are void of statistical properties (Chang et al., 2015).

Huang et al. (2014) propose a two-step stochastic frontier approach to estimate the group-specific frontiers and the metafrontier respectively, and advocate decomposing the efficiency scores of various groups into TE and technology gaps. The main difference with previous approaches lies in the second step. This method uses stochastic frontier techniques, ensuring statistical properties of stochastic frontier analysis in the estimation are retained. Also, this method directly estimates technology gaps and allows for the identification of the sources of variation among groups. Recently, a number of studies have employed the approach developed by Huang et al. (2014). They include Melo-Becerra and Orozco-Gallo (2015) who estimate and compare the technical efficiency for smallholder crop and livestock farmers in different production systems in Colombia. Chang et al. (2015) compare the technical efficiency of accounting firms between the US, China, and Taiwan.

3. Methodology

3.1. Analytical strategy

The metafrontier production function model for the farming households of different ecological regions is estimated by the two-step procedure suggested by Huang et al. (2014). Technical efficiency is derived by estimating a stochastic production frontier from each ecological region and for the metafrontier comprising the entire agricultural sector of Nepal, using the approach by Battese and Coelli (1995). For the *j*th region, the stochastic frontier of the *i*th farming household is modeled as,

$$Y_{ji} = f^{j}(X_{ji})e^{V_{ji}-U_{ji}}, \quad \text{where } U_{ji} \sim N\ [\delta_j Z_{ji}, \sigma^2] \tag{1}$$

where $j = 1,2,\ldots,J$; $i = 1,2,\ldots,N$ and where Y_{ji} and X_{ji} respectively denote the output and input vector of the *i*th farming household in the *j*th region. Following standard stochastic frontier modeling, V_{ji} is a normally distributed random variable with zero mean and variance σ^2 and which represents statistical noise. The non-negative random errors U_{ji} represent technical inefficiency and δ_j ($j = 1,2,\ldots,J$) is the region specific parameter vector to be estimated.[2] U_{ji}, follows a truncated normal distribution and is assumed to be independent of V_{ji}. Z_{ji} is the exogenous vector of variables determining inefficiency specific to each farming household within each region. A farming household's technical efficiency is then defined as:

$$TE_i^j = \frac{Y_{ji}}{f^{j}(X_{ji})e^{V_{ji}}} = e^{-U_{ji}} \tag{2}$$

The common metafrontier production function for all regions is defined as $f^{M}(X_{ji})$, where the function is the same for all regions. This metafrontier envelops all individual region's frontiers $f^{j}(X_{ji})$, which is expressed by the following relationship:

$$f^{j}(X_{ji}) = f^{M}(X_{ji})e^{-U_{ji}^{M}}, \forall\ j,\ i \tag{3}$$

where $U_{ji}^{M} \geq 0$. Hence $f^{M}(.) \geq f^{j}(.)$ and the ratio of the *j*th region's production frontier to the metafrontier is defined as the technology gap

[2] See Battese and Coelli (1995) for detailed specification and interpretation of parameters.

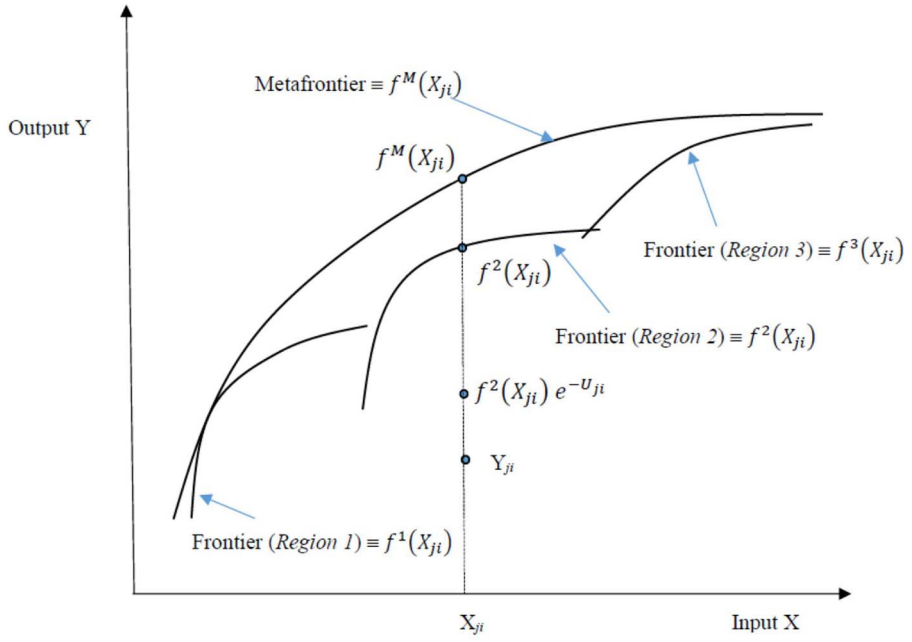

Fig. 2. Metafrontier production functions for different ecological regions. Prepared by the authors based on Battese et al. (2004) and Huang et al. (2014).

ratio (TGR). This can be represented by:

$$TGR_i^j = \frac{f^j(X_{ji})}{f^M(X_{ji})} = e^{-U_{ji}^M} \leq 1 \tag{4}$$

Fig. 2 illustrates the metafrontier production model. At a given input level X_{ji}, − a farming household's observed output Y_{ji} with respect to the metafrontier $f^M(X_{ji})$ − has three components: the TGR, the farming household's technical efficiency, and the random noise component. That is:

$$\frac{Y_{ji}}{f^M(X_{ji})} = TGR_i^j \times TE_i^j \times e^{V_{ji}} \tag{5}$$

As the random noise component is obtained from the stochastic frontier estimation, the decomposition in (5) can be expressed as:

$$MTE_{ji} = \frac{Y_{ji}}{f^M(X_{ji})e^{V_{ji}}} = TGR_i^j \times TE_i^j \tag{6}$$

where, MTE_{ji} is defined as the household's technical efficiency with respect to the metafrontier production technology.

The method proposed by Huang et al. (2014) using the stochastic frontier regression rather than the mathematical programming technique in the estimation of the metafrontier, specifically takes into account the estimation error of $\hat{f}^j(X_{ji})$ in estimating $f^j(X_{ji})$. Given the SFA estimates of the region-specific frontiers are $\hat{f}^j(X_{ji})$ for all $j = 1,2,\ldots J$ regions, then the estimation error of the region-specific frontier is:

$$\ln\hat{f}^j(X_{ji}) - \ln f^j(X_{ji}) = e_{ji} - \hat{e}_{ji} \tag{7}$$

Defining the estimated error as $V_{ji}^M = e_{ji} - \hat{e}_{ji}$, the relation to the metafrontier can be written as:

$$\ln\hat{f}^j(X_{ji}) = \ln f^M(X_{ji}) - U_{ji}^M + V_{ji}^M, \forall\, i, j = 1, 2, \ldots, J \tag{8}$$

Eq. (8) resembles the conventional stochastic frontier regression, and is therefore called the stochastic metafrontier (SMF), in which the technology gap component $U_{ji}^M \geq 0$ is assumed to be distributed as truncated-normal, i.e., $U_{ji}^M \sim N^+(\mu^M(Z_{ji}^M), \sigma_u^{M2}(Z_{ji}^M))$, and independent of V_{ji}^M. The mean $\mu^M(Z_{ji}^M)$ is a function of environmental variable vector Z_{ji}^M, of the ith farming household, in the jth region, and the heteroscedastic variance $\sigma_u^{M2}(Z_{ji}^M)$ reflects the production uncertainty.

Thus, the metafrontier estimation approach proposed by Huang et al. (2014) can be summarized in the estimation of the two following regressions,

$$\ln Y_{ji} = \ln f^j(X_{ji}) + V_{ji} - U_{ji}, \quad i = 1, 2, \ldots, N_j; \tag{9}$$

$$\ln\hat{f}^j(X_{ji}) = \ln f^M(X_{ji}) + V_{ji}^M - U_{ji}^M \tag{10}$$

where $\ln\hat{f}(X_{ji})$ is the estimates of the region-specific frontier. This should be estimated J times, one for each region. The estimates from all J regions are then pooled to estimate the metafrontier (Eq. (10)). To ensure that the metafrontier is larger than or equal to the region-specific frontiers (Fig. 2) ($\ln f^j(X_{ji}) \leq \ln f^M(X_{ji})$), the estimated TGR must always be less than or equal to unity.

$$\hat{TGR}_i^j = \hat{E}\left(e^{-U_{ji}^M} | \hat{e}_{ji}^M\right) \leq 1 \tag{11}$$

where $\hat{e}_{ji}^M = \ln\hat{f}^j(X_{ji})$. $\ln\hat{f}^M(X_{ji})$ are the estimated composite residuals of Eq. (10). The estimated technology gap ratio is a function of the production environment variable vector Z_{ji}^M, with a mean of $\mu^M Z_{ji}^M$ and heteroscedastic variance of $\sigma_u^{M2} Z_{ji}^M$. The corresponding estimated metatechnical efficiency (MTE) is equal to the product of the estimated TGR and the estimated individual farming household's technical efficiency:

$$\hat{MTE}_i^j = \hat{TGR}_i^j X\ \hat{TE}_i^j \tag{12}$$

3.2. Study area

Topographically, Nepal is broadly divided into three regions: the Terai in the south, the Hill in the center and the Mountain in the north. These regions are characterized by distinct agro-ecological and climatic conditions determining different production potentials. The Terai constitute 35% of total land in the country of which about 38% is cultivated and is of relatively high agricultural potential. The region consists of flat land that extends from 60 m above sea level (masl) up to 800 masl. The most important crops grown are paddy, wheat, and maize. The Hill region constitutes 42% of total land of which about 15% is cultivated. The region comprises steeply sloped lands with several small valleys and is in the range of 800–4,877 masl. Maize, paddy, and wheat are the most important crops grown. The Mountain region constitutes 23% of total land area of which about 4% is cultivated. The region ranges in altitude from 4877 to 8848 masl and consists of steeply sloped lands

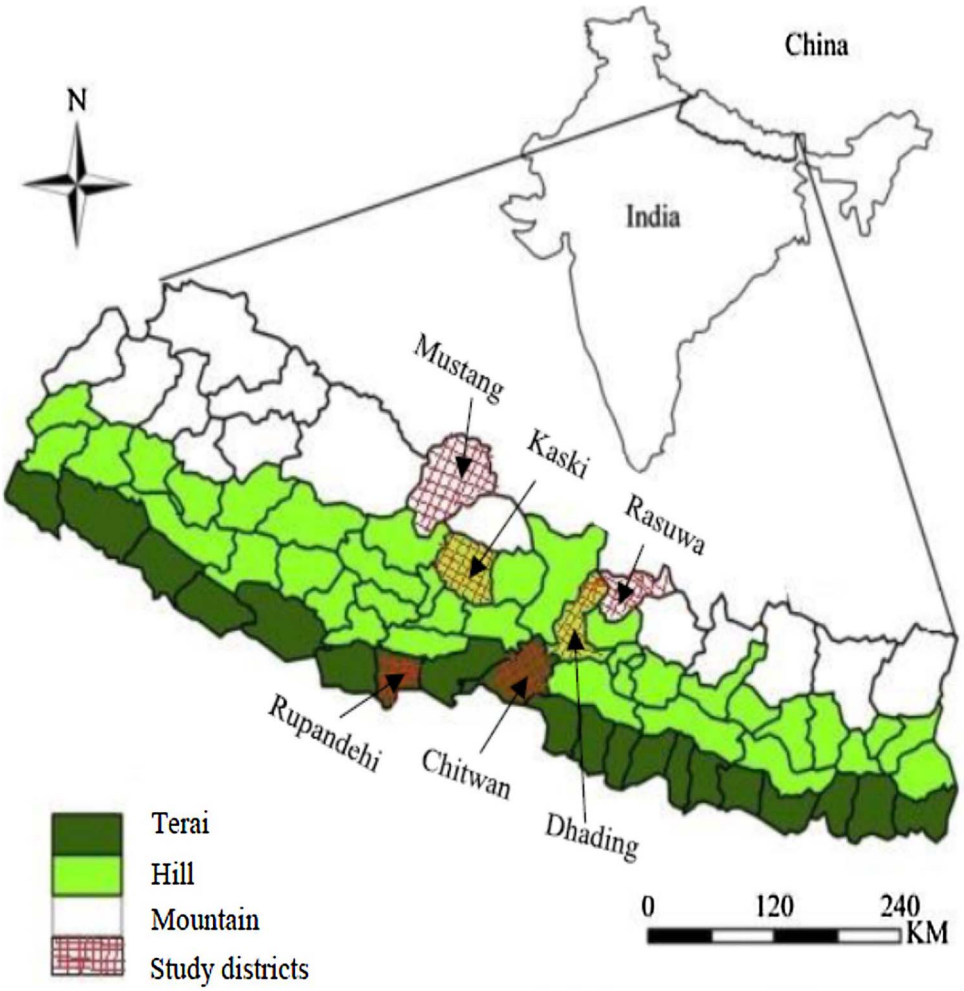

Fig. 3. Map of Nepal showing the ecological regions and the study districts.

and snow covered mountains with few valleys. Barley, wheat, and buckwheat are the major crops grown in this region with livestock also playing an important role. Although these regions are distinct in terms of geography and climate, farmers in all the regions grow crops such as maize, wheat, buckwheat, mustard, lentils etc. In addition, farmers employ many similar management practices in crop production, providing opportunities to learn and exchange agricultural techniques across the regions.

Administratively, Nepal is divided into 75 districts. In this research, two districts from each ecological region were selected: Mustang and Rusuwa from the Mountain region; Kaski and Dhading from the Hill region, and Chitwan and Rupandehi from the Terai region (Fig. 3). The field study was conducted by means of randomly selecting two village development committees (VDCs)[3] in each district. The unit of analysis is the farming household, a key decision-making unit in the agricultural production process. The selection of farming households from the VDC involved two steps. First, four wards in each VDC were selected randomly. We obtained the list of households in the selected wards from the office of the VDC. Then, we identify households involved in farming in each randomly selected ward.[4] In the next step, we selected 15 farming households from each ward using simple random sampling, producing a total sample size of 720. Out of the 720, we had to exclude 16 observations during the analysis due to missing information on inputs and outputs.

The household survey was carried out through a face-to-face interview with the decision maker of the sampled farming households, who could be an adult of any gender. The interview was conducted in Nepali language and took approximately one hour to complete. We recruited four enumerators[5] from the Agriculture and Forestry University in Nepal for the household survey. Prior to conducting the household survey, the enumerators were given a training on how to collect data appropriately. They were briefed on the context, purpose and expected outcome of the study. Each question in the questionnaire was discussed in the training and it was confirmed that enumerators understand all the questions. Furthermore, they were made aware of the confidentiality of the collected data.

3.3. Data

Data on inputs and outputs used in agricultural production and other socio-economic characteristics, are drawn from the household survey. Selection of variables follows the existing literature (Rahman and Rahman, 2009; Chen et al., 2009; Mishra et al., 2015; Gedara et al., 2012; Rahman, 2010). The output variable is measured by the total value of agricultural production in Nepalese rupees (NRs). It is the sum

[3] A VDC is an administrative unit in Nepal similar to a municipality.

[4] We asked four to five village persons to identify the households involved in farming. People in villages in Nepal are familiar with almost all families in the villages. So, listing of households involved in farming is a relatively easy task for them.

[5] All the recruited enumerators had completed their bachelor degree in agricultural science. We selected agriculture graduates as the major portion of the questionnaire included questions related to agriculture.

Table 1
Descriptive statistics.

	Terai		Hill		Mountain	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Production value (NRs)	70737.614	30942.589	46396.455	34226.219	33893.480	25097.174
Total land (hectare)	0.763	0.413	0.549	0.357	0.357	0.286
Total labour (man-days)	57.142	50.788	83.013	67.882	36.572	26.937
Total chemical fertilizer (kg)	260.909	167.133	62.732	50.757	85.355	75.600
Total capital (NRs)	3925.621	2439.959	4953.750	4890.132	3707.041	3581.884
Gender (female)	0.446	0.497	0.285	0.452	0.332	0.472
Education (years)	8.083	4.208	7.400	3.846	7.384	4.540
Farming experience (years)	22.729	12.806	27.562	14.393	22.131	12.357
Sold produce (dummy;1 = yes)	0.692	0.460	0.630	0.485	0.231	0.423
Adaptation (index)	99.008	96.393	115.140	75.085	56.993	46.492
Distance to market (km)	5.218	5.849	12.647	15.164	6.365	5.693
Share of irrigated land (%)	86.567	20.424	66.591	28.855	58.883	28.504
non-farm income (dummy;1 = yes)	0.750	0.433	0.745	0.437	0.546	0.499
Participation (dummy;1 = yes)	0.854	0.353	0.417	0.494	0.786	0.411
Aafected by drought or flood (dummy; 1 = yes)	0.428	0.355	0.294	0.277	0.346	0.245
Number of observations	240		235		229	

of the value of all the cereal, leguminous and oil seed crops produced by a household in the year 2014/15. The actual quantity of production was obtained through the household survey whereas the output price was obtained through focus group discussions in each village. Thus, we assume equal output price between farmers in a specific village. The output includes value of both sold quantities and that kept in the house for family consumption. We collected data on actual crop production in kilogram. However, we choose to use the aggregate output in value terms because the majority of households produce more than one crop. In our sample, on average, a farming household produces three different crop species. Inputs include the area of land under cultivation measured in hectares, labour used in crops production measured in man-days, the quantity of fertilizers used measured in kilogram and capital input measured in Nepalese Rupees (NRs) respectively in the year 2014/15. Capital input includes the expenditure on irrigation, pesticides, seeds etc.

As mentioned in the methodology section, the empirical analysis takes into account the effect of environmental variables. In the first stage of the estimation, these variables explain the differentials in technical efficiency of the farming households with respect to the region-specific frontier. Selection of the variables is based on existing literature (e.g., Chen et al., 2009; Coelli and Fleming, 2004; Rahman, 2011; Binam et al., 2004; Omonona et al., 2010; Theriault and Serra, 2014; Ho et al., 2017). A total of five variables representing socio-economic characteristics of the farming households are included in the inefficiency effects model. These variables include gender of the household head, farming experience of household head in years, education of household head in years, whether the household sold agricultural produce in the last year or not, and the adaptation index. This index is constructed taking into account different types of adaptation practices adopted by farming households in their farm land to minimize the adverse impacts of climate change such as drought and flood. The index takes into account the number of adaptation practices adopted by the particular farming household and the effectiveness of the adaptation practices (Appendix A). Initially we also included the age of the household head and the total number of crops grown. However, in our sample data we found a strong correlation between age and farming experience, and number of crops and adaptation. Age and number of crops were therefore excluded in our data in favour of farming experience and the adaptation index.

For estimation of the second stage of the metafrontier, five environmental variables which contribute to explaining technological gap ratios are included. These variables include distance to market from the household in kilometers, share of irrigated land calculated as the percentage of irrigated land to the total cultivated land, and membership in a farmers' group or association. The latter variable is measured as a dummy variable that takes the value 1 if any member of a household is a member of a farmers' group or association. Additionally, we included a variable that capture whether a farming household experiences the effect of drought or flood in their farmland in the last five years. We do so given that a significant percentage of farmlands in Nepal have faced either drought and/or flood in recent years.[6] Lastly, to take into account income source diversification, we included non-farm sources of income as a dummy variable that takes the value 1 if the household has income from non-farm sources.

Table 1 shows the means and standard deviations of the variables used for the empirical analysis. From this information, it can be observed that farming households in the Terai region have, on average, the highest level of production and cultivated land, the highest level of chemical fertilizer use, the best education levels and highest use of irrigated land. Similarly, the Terai region has the highest percentage of farming households associated with farmers groups, diversified sources of income, and sold agricultural produce. Farming households in the Hill region have on average the highest distance from household to market, adaptation index, labour use, and capital use. However, it is worth noting that there is a wide dispersion in these variables within all the regions.

4. Results and discussion

As explained above, we used Battese and Coelli's (1995) model to estimate the region specific stochastic frontiers. To characterize the production technology, the adequacy of the Cobb-Douglas functional form was tested against the less restrictive translog form. The Cobb-Douglass specification provided the more consistent set of results for different ecological regions. It should be noted that the Cobb-Douglas functional form has been widely used in efficiency analyses in agriculture (Manjunatha et al., 2013; Binam et al., 2004; Battese, 1992; Mayen et al., 2010).

To examine whether the three regions share the same technology, a

[6] Nepalese farmers grow crops under uncertain environments with rain-fed farming accounting for nearly two-thirds of the cultivated area (MoAD, 2015). Changing climate and the resultant prolonged droughts and unseasonal rains affect much of Nepal's agricultural production. For example, due to unfavourable weather conditions in 2012/13, rice, maize and millet production fell by 11.3%, 8.3% and 3.0% respectively compared to the previous year (MoF, 2013). In 2013/14, rice could not be planted in an area covering around 50,000 ha due to inadequate rainfall (MoF, 2014).

Table 2
Estimated parameters for the agro-ecological region frontiers.

Variables	Terai		Hill		Mountain	
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
Production frontier						
Constant	3.679***	0.294	4.721***	0.348	2.921***	0.977
Ln (land)	0.099*	0.052	0.293***	0.065	0.133	0.152
Ln (labour)	0.329***	0.077	0.306***	0.064	0.828***	0.162
Ln (fertilizer)	0.063	0.039	0.041	0.039	0.006	0.058
Ln (capital)	0.393***	0.054	0.155***	0.051	0.108*	0.052
Environmental variables						
Constant	1.692***	0.332	1.443*	0.656	1.360*	0.679
Gender	0.915	0.528	−0.188	0.210	0.424	0.409
Education	−0.112**	0.043	−0.012	0.027	−0.159***	0.061
Farming experience	−0.006	0.006	−0.051**	0.018	−0.021	0.015
Sold produce	1.159	0.718	−0.461***	0.151	0.565	0.353
Adaptation	−0.526***	0.144	−0.395**	0.177	−0.354*	0.181
Sigma-squared	0.455***	0.110	0.374***	0.057	1.040***	0.190
Gamma	0.524***	0.185	0.439***	0.120	0.403**	0.173
Log (likelihood)	−210.389		−190.576		−310.503	

***,** and * denote 1%, 5% and 10% level of statistical significance.

Table 3
Technical efficiency derived from the region-specific frontiers.

	Terai		Hill		Mountain	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
By ecological regions	0.858	0.086	0.806	0.117	0.778	0.156
By production value (median as a cut-off point)						
High	0.874	0.063	0.848	0.075	0.865	0.064
Low	0.835	0.109	0.740	0.139	0.744	0.167
By farm size						
Large	0.861	0.078	0.825	0.091	0.866	0.088
Small	0.853	0.086	0.777	0.143	0.743	0.163
By number of crops						
More (> 3)	0.898	0.043	0.870	0.074	0.856	0.087
Few (< 3)	0.846	0.093	0.796	0.119	0.721	0.169
By purpose of production						
Also for sale	0.834	0.092	0.847	0.077	0.772	0.167
Only for family consumption	0.913	0.028	0.737	0.139	0.779	0.152

likelihood-ratio (LR) test was calculated. The null hypothesis of the test is that the stochastic production frontier models for the three regions are the same for all households. To test the hypothesis, we first estimated the stochastic frontiers for each regions. Then we estimated the stochastic frontier including households from all three regions. Following Battese et al. (2004), the likelihood-ratio statistic is defined by $\lambda = -2\,[\ln L(H_0) - \ln L(H_1)]$, where $\ln L(H_0)$ is the value of the log likelihood function for the stochastic frontier estimated by pooling the data for all regions. Ln $L(H_1)$ is the sum of the values of the log likelihood functions of the three regional production frontiers. The statistical value of the likelihood-ratio test is 211.84, which is significant as it is greater than the critical value of Chi-squared distribution with degrees of freedom given by the difference between the number of parameters estimated under H_1 and H_0 (i.e. 33–11 = 22). This suggests that the stochastic frontier for the three ecological regions is not the same and indicates the necessity to estimate efficiency measures relative to the metafrontier production function.

Table 2 presents the estimated parameters and standard errors for the different ecological regions. In all three frontiers, the estimated mean output elasticities of all the inputs have positive signs with most of them highly significant, indicating a positive and significant relationship between inputs and the output. Additionally, the sum of the estimated parameters associated with all the inputs is less than one in all the regional frontiers, implying decreasing returns to scale. Although the decreasing returns to scale is common in agricultural production (Neumann et al., 2010), this finding is in contrary to our expectation as the farmers in the study area are mostly smallholders with the average land holding size of 0.557 ha (Table 1). This may be due to the application of the restrictive Cobb-Douglas model in representing technologies. Anderson and Jodha (1973) argued that the Cobb-Douglas model seems questionable particularly in the study of phenomena related to farm size. Furthermore, our results indicate a positive relationship between farm size and technical efficiency (Table 3).

The variance of the error term is explained by the inefficiency terms in all three models.[7] For environmental variables, gender of the household's head was not significant in any of the regions. Other environmental variables show the expected signs for the different regions. In particular, education of the household head has a positive and significant effect on efficiency of farming households in the Terai and Mountain regions. In the hill region, household heads with more farming experience and households that were involved in selling agricultural products are found to be more efficient compared to those with less farming experience and not involved in selling agricultural produce. Adaptation has positive and significant effects on efficiency of farming households in all three regions.

The technical efficiency measures for all farming households in respective regions were calculated from the estimation of the region-specific stochastic frontiers. Mean TE estimates vary between the regional frontiers. Table 3 shows the means and standard deviations of efficiency measures by ecological region, production value, farm size, number of crops grown, and whether the household produce only for family consumption or for selling. Results indicate that, on average, Terai has the highest technical efficiency (86%), followed by Hill (81%), and Mountain (78%). This does not imply that households in the

[7] The gamma parameter which measures the relevance of inefficiency with respect to the random noise (which accounts for differences between the observed output and the estimated frontier), is significant for all three cases. The existence of an inefficiency effect was tested for using the likelihood-ratio test defined by $\lambda = -2\,[\ln L(H_0) - \ln L(H_1)]$, where $\ln L(H_0)$] and $\ln L(H_1)$ denote the values of the log likelihood function under the null (H_0) and alternative (H_1) hypotheses respectively. The null hypothesis (H_0) here was that all the coefficients of the explanatory variables in the inefficiency model are equal to zero i.e. technical inefficiency effects have a half-normal distribution. The results obtained indicate that the null hypothesis of no technical inefficiencies is strongly rejected for all three regions. The LR statistics are 23.3, 17.4, and 19.4 for Terai, Hill and Mountain regions respectively. All these values are greater than the critical value (10.37) at the 5% level of significance. Here the degree of freedom is the difference in number of parameters in null and alternative hypotheses i.e. 11 − 6 = 5. Critical values were taken from Table 1 of Kodde and Palm (1986).

Table 4
Estimated parameters for the metafrontier.

Variables	Coefficient	SE
Production frontier		
Constant	4.853***	0.088
Ln (land)	0.199***	0.011
Ln (labour)	0.256***	0.013
Ln (fertilizer)	0.107***	0.008
Ln (capital)	0.281***	0.016
Environmental variables		
Constant	0.709***	0.162
Distance to market	0.011***	0.002
Share of irrigated land	−0.001	0.003
Non-farm income	−0.350***	0.081
Participation	−0.226**	0.100
Affected by drought or flood	−0.117	0.093
Sigma-squared	0.414***	0.083
Gamma	0.970***	0.003
Log (likelihood)	−121.186	

***,** and * denote 1%, 5% and 10% level of statistical significance.

Mountain region have lower TE performance than the Hill and Terai regions as these TE scores across regions are not comparable to each other. The standard deviation shows that there is a great dispersion in efficiency measures among households within the ecological regions. Furthermore, results indicate that households with higher production value and large farm size have a higher measure of efficiency and less dispersion in the data in all three regions. This may be due to farmers with small plots practicing more intensive cultivation resulting in deterioration of land quality and sub-optimal allocation of inputs. Our results are similar to the findings of studies by Rahman and Rahman (2009) in Bangladesh, Manjunatha et al. (2013) in India and Bojnec and Latruffe (2013) in Slovenia all of which find an inverse relationship between land fragmentation and efficiency in crop production.

Our results reveal that farming households who grow a greater diversity of crops have a higher measure of efficiency and less dispersion in the data in all three regions. This finding is in support of the argument that crop diversification widens the choice of crop production, minimizes the risk of crop failure and enhance input use efficiency. Our results are consistent with the findings of Rahman (2009) in Bangladesh, Manjunatha et al. (2013) in India and Ogundari (2013) in Nigeria who find a positive impact of crop diversification on productivity and efficiency.

We used the estimates obtained from the region specific frontiers to estimate the metafrontier of the agricultural sector. Table 4 shows the coefficients and standard error of the estimated parameters for the metafrontier. All the input coefficients are significant and have the expected signs. As in the region specific models, the LR test of the existence of inefficiency effects indicate that the null hypothesis of no technical inefficiencies should be rejected.[8] Regarding environmental variables, the farther away the household is located from the market, the further apart is the production frontier from the metafrontier. This is an indication of the importance of market access in reducing the technology gap faced by some households and regions. Our finding is in line with the previous studies that find a positive impact of increased market access on adoption of agricultural technologies by smallholder farmers (Hassan and Nhemachena 2008; Shiferaw et al., 2009).

Farming households which receive non-farm income, on average, operate under a superior technology compared to households involved only in farming activities. This may be due to that situation that involvement in non-farm activities minimizes the credit constraints for adoption of technologies on farm. This finding is consistent with that of Ransom et al. (2003) in Nepal, Chirwa (2005) in Malawi and Tambo and Abdoulaye (2012) in Nigeria. Furthermore, households with it members engaged in agricultural related institutions are operating under a superior technology compared to those not associated with such institutions. Our result upholds the findings of previous studies in Nepal (Neupane et al., 2002; Khanal et al., 2017) and Ethiopia (Teklewold et al., 2013) which reveal a positive impact of local institutions on technology adoption in agriculture. These findings indicate the importance of income source diversification, and formation and promotion of agricultural related groups and associations in minimizing the technology gap experienced by farming households in Nepal.

Presented in Table 5 are: the means and standard deviations of the technological gap ratios (TGR) that correspond to the distance from the respective region-specific frontiers to the metafrontier. The meta technical efficiency (MTE) measures the distance from the *i*th farming household to the metafrontier; and the technical efficiency measures (TE) is derived from the region-specific production frontiers. The significance of measuring MTE is that it allows us to make efficiency comparisons of farming households across ecological regions (O'Donnell et al., 2008). Results show that the average TE, MTE and TGR are 81%, 57% and 70% respectively. The TE measures indicate that farming households could achieve significant gains in agricultural production efficiency if they operate at the most efficient levels within the region.

The results of MTE and TGR indicate that there is great scope for improving the performance of the agricultural sector as a whole. As indicated earlier, this could be achieved by improving farmers' access to markets, by increasing their participation in agricultural related organizations and through livelihood diversification. The Terai region has the highest TGR (87%) followed by the Hill region (74%) and the Mountain region (47%). This reveals that the maximum output that can be obtained using the production technology of the Mountain region is, on average, only 47% of the potential of the agricultural sector as a whole. These results suggest that farming households in the Terai region have advantages in the use of agricultural production technologies compared to households located in the Hill and Mountain regions. This may be due to the differences in geographical, infrastructure and resource endowments, and to climatic factors between Nepal's ecological regions. When efficiency scores are grouped by production value and farm size, farming households with a higher production value, and larger farm size tend to be closer to potential production defined by the metafrontier of the agricultural sector.

If the TE estimates relative to their own regional frontiers are compared with the metafrontier, the conclusions are contradictory. Households in the Terai region, on average, have a TE score of 86% with reference to its regional frontier, with 81% of households having an efficiency level of > 80% (Table 6). However, the metatechnical efficiency score (MTE) with respect to the metafrontier is 75%, with

Table 5
Technical efficiency for the agricultural sector.

	Technology gap ratio (TGR)		Technical efficiency by regions (TE)		Technical efficiency from the metafrontier (MTE)	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Total sector	0.696	0.205	0.815	0.127	0.574	0.199
By ecological regions						
Terai	0.866	0.101	0.858	0.086	0.745	0.116
Hill	0.744	0.102	0.806	0.117	0.599	0.115
Mountain	0.467	0.152	0.778	0.156	0.369	0.148
By production value						
High	0.752	0.171	0.862	0.069	0.649	0.161
Low	0.640	0.220	0.768	0.151	0.498	0.206
By farm size						
Large	0.746	0.163	0.847	0.090	0.632	0.154
Small	0.646	0.229	0.782	0.148	0.515	0.222

[8] The statistical value of the LR test is 55.7.

Table 6
Frequency distribution of TGR, TE and MTE by ecological regions.

Level	Terai			Hill			Mountain		
	TGR	TE	MTE	TGR	TE	MTE	TGR	TE	MTE
(0.9–1.0)	119 (49.58%)	91 (37.91%)	6 (1.67%)	15 (6.38%)	49 (20.85%)	5 (2.13%)	4 (1.75%)	40 (17.47%)	3 (1.31%)
(0.8–0.9)	76 (31.67%)	105 (43.75%)	91 (37.92%)	57 (24.26%)	106 (45.11%)	13 (5.53%)	5 (2.18%)	101 (44.10%)	6 (2.62%)
(0.7–0.8)	26 (10.83%)	29 (12.08%)	74 (31.67%)	71 (30.21%)	41 (17.45%)	38 (16.17%)	10 (4.37%)	35 (15.28%)	10 (4.37%)
(0.6–0.7)	9 (3.75%)	12 (5.00%)	43 (17.92%)	86 (36.60%)	20 (8.51%)	69 (29.36%)	19 (8.30%)	24 (10.48%)	12 (5.24%)
Below 0.6	10 (4.17%)	3 (1.25%)	26 (10.83%)	6 (2.55%)	19 (8.09%)	110 (46.81%)	191 (83.41%)	29 (12.66%)	198 (86.46%)

only 39% of the households having an MTE score of > 80%. Similarly, in the Hill and Mountain regions substantial differences are exhibited in efficiency scores obtained with respect to the regional frontiers and metafrontiers.

5. Conclusion

This paper estimates and compares the technical efficiency of farming households in three different ecological regions of Nepal. The empirical analysis is carried out by employing the stochastic metafrontier approach. This approach allows us to compare technical efficiency when production takes place under different technological condition. Technical efficiency scores obtained from the regional frontiers and the metafrontier indicate that farming households in Nepal could achieve significant gains in agricultural production. On average, the technical efficiency derived from the regional frontier is 81%; technical efficiency from the metafrontier is 57%, and the technological gap ratio is 70%. The higher efficiency measures in the Terai region obtained from the metafrontier suggests that farming households in the Terai regions could nevertheless benefit from better production conditions. In summary, we found that farming households in the three ecological regions of Nepal do not share the same production technology.

We find that in the Nepalese crop sector, there is a substantial opportunity to increase performance through technical efficiency improvement within ecological regions. Furthermore, the results suggest that there is room to improve crop production by switching technologies across the ecological regions. Consequently, agricultural policies for increasing production should focus both on efficiency improvement and technological progress. The regional frontier results equally indicate that there is an opportunity to improve the performance of farming households within the regions. This could be achieved by designing and implementing programs that improve the education level, farming experiences, and dissemination of agricultural practices that minimize climate change impacts in agriculture. Second, the metafrontier results indicate that policies should be developed to reduce the technology gap between particular regions and for the agricultural sector as a whole.

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Appendix A. Adaptation index

We first identified the adaptation practices those that were used by farmers in the study area through a review of the literature and the focus group discussions with farmers in respective villages. The practices that had been implemented by farmers for many years without reference to climate change impacts were not taken into consideration. Then we conducted stakeholders' workshops in each agro-ecological region to assign weights to adaptation practices. The participants in the workshops were local agricultural and extension experts from governmental and non-governmental organizations, leader farmers and key informants in the area. Through thorough interactions with stakeholders' participants, scores were assigned for each adaptation in relation to effectiveness, feasibility and sustainability. A 10 point Likert scale was used for rating the practices based on all three criteria; 10 representing very effective and 0 being not effective at all. Similarly scores for feasibility and sustainability were given based on a 10 points scale. These three scores were then added to obtain the total weight of an adaptation practices. Through the household survey, we assess the actual adaptation practices used by farmers on their farm lands.

Following Below et al. (2012) we calculated adaptation as the sum of the weighted adaptation practices of the farmer:

$$AI_j = w_1 v_{1j} + \ldots\ldots\ldots w_n v_{nj}$$

Where,AI_j = adaptation index of household j;w_1 = weighting factor of adaptation practice 1;v_{1j} = jth household value for practice 1 (which takes the value 1 if the jth household adopted practice 1 and 0 if not adopted).

References

Adhikari, Chandra Bahadur, Bjorndal, Trond, 2012. Analyses of technical efficiency using SDF and DEA models: evidence from Nepalese agriculture. Appl. Econ. 44 (25), 3297–3308.
Anderson, Jock R., Jodha, N.S., 1973. On Cobb-Douglas and related myths. Econ. Polit. Weekly A65–A66.
Battese, George E., Coelli, Tim J., 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data. Emp. Econ. 20 (2), 325–332.
Battese, George E., Rao, D.S. Prasada, 2002. Technology gap, efficiency, and a stochastic metafrontier function. Int. J. Bus. Econ. 1 (2), 87.
Battese, George E., Prasada Rao, D.S., O'donnell, Christopher J., 2004. A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. J. Product. Anal. 21 (1), 91–103.
Battese, George E., 1992. Frontier production functions and technical efficiency: a survey of empirical applications in agricultural economics. Agric. Econ. 7 (3), 185–208.
Below, Till B., Mutabazi, Khamaldin D., Kirschke, Dieter, Franke, Christian, Sieber, Stefan, Siebert, Rosemarie, Tscherning, Karen, 2012. Can farmers' adaptation to climate change be explained by socio-economic household-level variables? Glob. Environ. Change 22 (1), 223–235.
Bhattarai, Basundhara, Beilin, Ruth, Ford, Rebecca, 2015. Gender, agrobiodiversity, and climate change: a study of adaptation practices in the Nepal Himalayas. World Dev. 70, 122–132.
Binam, Joachim Nyemeck, Tonye, Jean, Nyambi, Gwendoline, Akoa, Mireille, 2004. Factors affecting the technical efficiency among smallholder farmers in the slash and burn agriculture zone of Cameroon. Food Policy 29 (5), 531–545.
Bojnec, Štefan, Latruffe, Laure, 2013. Farm size, agricultural subsidies and farm

performance in Slovenia. Land Use Policy 32, 207–217.
Chang, Bao-Guang, Huang, Tai-Hsin, Kuo, Chun-Yi, 2015. A comparison of the technical efficiency of accounting firms among the US, China, and Taiwan under the framework of a stochastic metafrontier production function. J. Product. Anal. 44 (3), 337–349.
Charnes, Abraham, Cooper, William W., Rhodes, Edwardo, 1981. Evaluating program and managerial efficiency: an application of data envelopment analysis to program follow through. Manage. Sci. 27 (6), 668–697.
Chen, Zhuo, Huffman, Wallace E, Rozelle, Scott, 2009. Farm technology and technical efficiency: evidence from four regions in China. China Econ. Rev. 20 (2), 153–161.
Chirwa, Ephraim W., 2005. Adoption of fertiliser and hybrid seeds by smallholder maize farmers in Southern Malawi. Dev. South. Africa 22, 1–12.
Coelli, Tim, Fleming, Euan, 2004. Diversification economies and specialisation efficiencies in a mixed food and coffee smallholder farming system in Papua New Guinea. Agric. Econ. 31 (2–3), 229–239.
Gedara, Kularatne Mohottala, Wilson, Clevo, Pascoe, Sean, Robinson, Tim, 2012. Factors affecting technical efficiency of rice farmers in village reservoir irrigation systems of Sri Lanka. J. Agric. Econ. 63 (3), 627–638.
Grosskopf, Shawna, Valdmanis, Vivian, 1987. Measuring hospital performance: a non-parametric approach. J. Health Econ. 6, 89–107.
Hassan, Rashid, Nhemachena, Charles, 2008. Determinants of African farmers' strategies for adapting to climate change: multinomial choice analysis. Afr. J. Agric. Resour. Econ. 2, 83–104.
Hayami, Yujiro, Ruttan, Vernon W., 1970. Agricultural productivity differences among countries. Am. Econ. Rev. 60 (5), 895–911.
Hayami, Yujiro, 1969. Sources of agricultural productivity gap among selected countries. American. J. Agric. Econ. 51 (3), 564–575.
Ho, Thong Quoc, Hoang, Viet-Ngu, Wilson, Clevo, Nguyen, Trung-Thanh, 2017. Which farming systems are efficient for Vietnamese coffee farmers? Econ. Anal. Policy 56, 114–125.
Huang, Cliff J., Huang, Tai-Hsin, Liu, Nan-Hung, 2014. A new approach to estimating the metafrontier production function based on a stochastic frontier framework. J. Product. Anal. 42 (3), 241–254.
Joshi, K.D., Conroy, C., Witcombe, J.R., 2012. Agriculture, Seed, and Innovation in Nepal: Industry and Policy Issues for the Future. Paper Presented at the International Food Policy Research Institute.
Khanal, Uttam, Wilson, Clevo, Hoang, Viet-Ngu, Lee, Boon, 2017. Impact of community-based organizations on climate change adaptation in agriculture: empirical evidence from Nepal. Environ. Dev. Sustain. 1–15.
Kodde, David A., Palm, Franz C., 1986. Wald criteria for jointly testing equality and inequality restrictions. Econometr.: J. Econometr. Soc. 1243–1248.
Månsson, Jonas, 1996. Technical efficiency and ownership: the case of booking centres in the Swedish taxi market. J. Trans. Econ. Policy 30 (1), 83–93.
Manjunatha, A.V., Anik, Asif Reza, Speelman, Stijn, Nuppenau, E.A., 2013. Impact of land fragmentation, farm size, land ownership and crop diversity on profit and efficiency of irrigated farms in India. Land Use Policy 31, 397–405.
Mayen, Carlos D., Balagtas, Joseph V., Alexander, Corinne E., 2010. Technology adoption and technical efficiency: organic and conventional dairy farms in the United States. Am. J. Agric. Econ. 92 (1), 181–195.
Melo-Becerra, Ligia Alba, Orozco-Gallo, Antonio José, 2015. Technical efficiency for Colombian small crop and livestock farmers: a stochastic metafrontier approach for different production systems. J. Product. Anal. 1–16.
Mishra, Ashok K., Mottaleb, Kh A., Khanal, Aditya R., Mohanty, Samrendu, 2015. Abiotic stress and its impact on production efficiency: the case of rice farming in Bangladesh. Agric. Ecosyst. Environ. 199, 146–153.
MoAD, 2015. Statistical Information on Nepalese Agriculture 2014/15: Government of Nepal, Ministry of Agricultural Development, Agri-Business Promotion and Statistics Division. Agri statistics Section, Singha Durbar, Kathmandu Nepal.
MoF, 2013. Economic Survey: Fiscal Year 2012/13. Ministry of Finance, Kathmandu, Nepal.
MoF, 2014. Economic Survey: Fiscal Year 2013/14. Ministry of Finance, Kathmandu, Nepal.
MoF, 2015. Economic Survey: Fiscal Year 2014/15. Ministry of Finance, Kathmandu, Nepal.
Moreira, Víctor H., Bravo-Ureta, Boris E., 2010. Technical efficiency and metatechnology ratios for dairy farms in three southern cone countries: a stochastic meta-frontier model. J. Product. Anal. 33 (1), 33–45.
Neumann, K., Verburg, P.H., Stehfest, E., Müller, C., 2010. The yield gap of global grain production: a spatial analysis. Agric. Syst. 103, 316–326.
Neupane, Ramji P., Sharma, Khem R., Thapa, Gopal B., 2002. Adoption of agroforestry in the hills of Nepal: a logistic regression analysis. Agric. Syst. 72, 177–196.
O'Donnell, Christopher J., Prasada Rao, D.S., Battese, George E., 2008. Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. Empir. Econ. 34 (2), 231–255.
Ogundari, Kolawole, 2013. Crop diversification and technical efficiency in food crop production: a study of peasant farmers in Nigeria. Int. J. Social Econ. 40, 267–287.
Ogundari, Kolawole, 2014. The paradigm of agricultural efficiency and its implication on food security in Africa: what does meta-analysis reveal? World Dev. 64, 690–702.
Omonona, Bolarin T., Egbetokun, O.A., Akanbi, A.T., 2010. Farmers resource-use and technical efficiency in cowpea production in Nigeria. Econ. Anal. Policy 40 (1), 87–95.
Paudel, Pashupati, Matsuoka, Atsushi, 2009. Cost efficiency estimates of maize production in Nepal: a case study of the Chitwan district. Agric. Econ. Czech 55 (3), 139–148.
Piya, S., Kiminami, A., Yagi, H., 2012. Comparing the technical efficiency of rice farms in urban and rural areas: a case study from Nepal. Trends Agric. Econ. 5, 48–60.
Poudel, K.L., Johnson, Thomas G., Yamamoto, Naoyuki, Gautam, Shriniwas, Mishra, Bhawani, 2015. Comparing technical efficiency of organic and conventional coffee farms in rural hill region of Nepal using data envelopment analysis (DEA) approach. Organ. Agric. 5 (4), 263–275.
Rahman, Sanzidur, Rahman, Mizanur, 2009. Impact of land fragmentation and resource ownership on productivity and efficiency: the case of rice producers in Bangladesh. Land Use Policy 26 (1), 95–103.
Rahman, Sanzidur, 2009. Whether crop diversification is a desired strategy for agricultural growth in Bangladesh? Food Policy 34, 340–349.
Rahman, Sanzidur, 2010. Women's labour contribution to productivity and efficiency in agriculture: empirical evidence from Bangladesh. J. Agric. Econ. 61 (2), 318–342.
Rahman, Sanzidur, 2011. Resource use efficiency under self-selectivity: the case of Bangladeshi rice producers. Aust. J. Agric. Resour. Econ. 55 (2), 273–290.
Ransom, Joel K., Paudyal, K., Adhikari, K., 2003. Adoption of improved maize varieties in the hills of Nepal. Agric. Econ. 29, 299–305.
Shiferaw, Bekele A., Julius, Okello, Ratna, V. Reddy, 2009. Adoption and adaptation of natural resource management innovations in smallholder agriculture: reflections on key lessons and best practices. Environ. Dev. Sustainability 11, 601–619.
Tambo, Justice Akpene, Abdoulaye, Tahirou, 2012. Climate change and agricultural technology adoption: the case of drought tolerant maize in rural Nigeria. Mitig. Adapt. Strateg. Glob. Change 17, 277–292.
Teklewold, Hailemariam, Kassie, Menale, Shiferaw, Bekele, 2013. Adoption of multiple sustainable agricultural practices in rural Ethiopia. J. Agric. Econ. 64 (3), 597–623.
Theriault, Veronique, Serra, Renata, 2014. Institutional environment and technical efficiency: a stochastic frontier analysis of cotton producers in West Africa. J. Agric. Econ. 65 (2), 383–405.
Villano, R., Boshrabadi, H. Mehrabi, 2010. When is metafrontier analysis appropriate? An example of varietal differences in Pistachio production in Iran. J. Agric. Sci. Technol. 12, 379–389.
Villano, Renato, Bravo-Ureta, Boris, Solís, Daniel, Fleming, Euan, 2015. Modern rice technologies and productivity in The Philippines: disentangling technology from managerial gaps. J. Agric. Econ. 66 (1), 129–154.